15.5 TIME-FREQUENCY DETECTION OF EEG ABNORMALITIES [0]

This article presents an example of time-frequency methodology used for the detection of seizures in recorded EEG signals. The techniques used are adapted to the case of newborn EEGs, which exhibit some well defined features in the time-frequency domain that allow an efficient discrimination between abnormal EEGs and background.

15.5.1 EEG Abnormalities and Time-Frequency Processing

Neonatal seizures are usually the first signs of neurological abnormalities and can lead to permanent brain damage or even fatalities if not detected at the early stages. There are a number of disturbances underlying the seizure rather than a single identifiable cause making the identification process difficult. The problem in newborn is harder than in adults because the more obvious clinical symptoms such as muscle spasms, sporadic eye movements and drooling are often difficult to detect [1]. For this reason, Electroencephalogram (EEG) is practically the only tool available in seizure detection and characterization in newborns. Three major approaches have been used to detect seizures in newborns based on the assumption that the EEG signals are stationary or at least locally stationary [1, 2]. However, a detailed examination of these signals shows that EEG signals exhibit significant non-stationary and multi-component features [see Fig. 15.5.1(a)]. making these three methods essentially invalid and at best only an approximation. This explains the relatively poor performance of these methods [2]. The non-stationarity and multicomponent nature of the EEG signal suggested the use of time-frequency (TF) signal processing to analyze and characterize the different newborn EEG patterns for developing a time-frequency seizure detection and classification [1, 3].

15.5.2 EEG Seizures in Newborns

A seizure is defined to occur when there is an excessive synchronous discharge of neurons within the central nervous system. Its manifestation in the EEG, known as electrographic seizure, consists of a paroxysmal events which are trains of rhythmic repetitive sharp waves that emerge more or less abruptly from the ongoing background activities and have a distinct beginning and end. They may start with low voltages that increase usually as the discharge progresses. They often contain subharmonics and may have polyphasic contours or be sinusoidal. These discharges pattern can be divided into four categories: focal spike and sharp waves (> 2Hz), local low frequency discharges (around 1Hz), focal rhythmic discharge (0.5 Hz - 15 Hz), and multifocal patterns (EEG discharge originating from two or more loci) [1].

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The duration of rhythmic discharges is highly variable, from as short as 1 second to as long as 30 minutes. This fact contributed to the disagreement between the researchers about what constitutes a seizure. In order to consider an EEG discharge as a seizure, some researchers require that it must last at least 10 seconds, others require a minimum of 20 seconds, while a third group does not specify a time limit.

Seizure patterns are occasionally corrupted by artifacts and some abnormal background patterns such as burst suppression (BS). The most noticeable artifacts are the ones caused by the heartbeat (ECG), the eye movement (EOG) and head and body movements (EMG) [4].

15.5.3 Data Acquisition

Electrical signals produced in the brain can be monitored in a non-invasive manner by measuring variations in potential on the scalp. This EEG measurement is achieved by strategically placing several small electrodes on the scalp. One electrode, usually at the base of the skull, acts as a reference (ground) signal, and various channels of data are created by measuring the voltage differences between neighboring electrodes. Five channels of EEG have been recorded in each session using the 10-20 International System of Electrode Placement. The EEG data has been recorded using a sampling frequency of 256 Hz. For artifact detection, three auxiliary signals representing electro-oculogram (EOG), electrocardiogram (ECG), and respiration are also recorded. Data used has been collected at the Royal Women's Hospital Perinatal Intensive Care Unit in Brisbane, Australia. The EEG signals containing seizures were obtained from two different newborn babies that have been clinically identified to have seizures. The gestational ages of the babies were 35 weeks and 40 weeks and 3 days. The recording lasted 137 minutes and 23 minutes respectively.

15.5.4 Selection of a Time-Frequency Distribution

The following characteristics were found to be typical of neonatal EEG signals [1]: non-stationary, occasionally multicomponent, low frequency signals in the range 0 to 5 Hz. These factors must be considered when selecting an optimal time-frequency distribution (TFD), as each TFD is more suited to representing signals with particular characteristics (see Chapter 3).

Since neonatal EEG signals are non-stationary and occasionally multicomponent, a desirable time-frequency distribution should have a good spectral resolution and reduced cross-terms. The performance and characteristics of several TFDs were compared to find an optimal representation of real neonatal EEG data in the TF domain. The scope of this comparison study has encompassed seven TFDs [1]. Each TFD has been applied to epochs of real neonatal EEGs for various data window lengths and individual TFD parameter values. The performances were compared visually and using an objective quantitative measure criterion (see Article 7.4). Based on this criterion, the B-distribution (BD) with the smoothing parameter β equals to 0.01 has been selected as the most suitable representation of

the EEG signals in the TF domain.

The B-distribution is defined in terms of its time-lag kernel (see chapters 2 and 3) and may be expressed as

$$\rho_z(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \left(\frac{|\tau|}{\cosh^2(t)}\right)^{\beta} z(t+\tau/2)z^*(t-\tau/2)e^{-j2\pi f\tau}\, du\, d\tau\,. \qquad (15.5.1)$$

The parameter β $(0 < \beta \leq 1)$ controls the sharpness of the cut-off of the two-dimensional filter in the ambiguity domain. Hence, the EEG signals were represented in time frequency using the B-distribution with a smoothing parameter of 0.01, a window length of 127 samples, and a time resolution of 5 samples. The data has been resampled to 20 Hz for better representation of low frequency regions. The time-frequency analysis was performed using the commercial *TFSA* 5.2 MATLAB$^{\text{TM}}$ toolbox (http://www.sprc.qut.edu.au//tfsa/∼index.html).

15.5.5 EEG Pattern Analysis

The visual analysis of the time-frequency EEG data led to divide the time-frequency EEG patterns into two classes: seizure and background. The seizure patterns can be characterized in the time-frequency domain by a main ridge (component) as either a linear FM law or a piecewise linear FM while the background patterns exhibit a low frequency burst activities or irregular activities with no clearly defined patterns [1]. These observations correlate well with clinical information related to EEGs [5]. Representative TF representations of each of the subclasses are detailed below.

15.5.6 Analysis of Time-Frequency Seizure Patterns

15.5.6.1 Linear FM (LFM) Patterns

The EEG seizures analyzed in the TF domain that can be approximated by linear FMs with either fixed or time-varying amplitudes can be classified into the following sub-classes:

LFM Patterns with a Quasi-Constant Frequency: Fig. 15.5.1(b) shows a seizure that has a linear FM behavior with an almost constant frequency. The amplitude of the time-frequency seizure pattern increases at the onset and decreases toward the end. A major advantage of the TF representation is that we can easily distinguish the seizure from other phenomena such as burst activities as long as they occupy different TF regions. These unwanted signals can be removed from the EEG signal using a well designed TF filter without affecting much the seizure signal.

LFM Patterns with a Decreasing Frequency: Fig. 15.5.1(c) of this class differs from the one above by the fact that its frequency decreases with time [5] . By looking at the TF behavior of the seizure, we can easily deduce the precise non-stationary character of the seizure. The classical detection methods based on the stationarity assumption will most likely miss these patterns.

15.5.6.2 Piecewise LFM Patterns

Most of the patterns analyzed so far can be approximated to a good degree of accuracy by piecewise linear FM as shown in Fig. 15.5.1(d). These types of seizures usually comprises the different stages of the seizure [4].

15.5.6.3 EEG Background Patterns

By background, we mean any signal that is not classified as seizure. Two distinct patterns have been noticed: Burst of activity and an irregular activity with no clear pattern.

Burst of Activity: Fig. 15.5.1(e) is an example of this class characterized by a burst of activity. These are a short period signals with a high energy lasting for few seconds and usually occurring at frequencies below 4 Hz. These features are characteristic of *burst suppression*. Burst suppression is defined as burst of high voltage activity lasting 1-10 seconds and composed of various patterns (delta (0 - 4 Hz) and theta (4 - 8 Hz) with superimposed and intermixed spikes, sharp waves, and faster activity) followed by a marked background attenuation [5].

Activity Lacking a Specific Pattern: Fig. 15.5.1(f) is an example of an EEG epoch lacking a well-defined and consistent pattern. These type of activities are not constrained within the low frequency bands characterizing the EEG seizure.

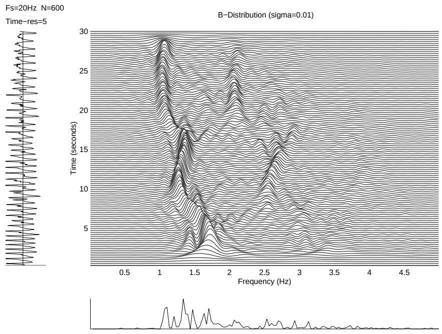
This time-frequency analysis indicates that a linear or piecewise linear instantaneous frequency (IF), obtained by taking the peak of the main component of a TFD, can be used as a critical feature of EEG seizure characteristics. These findings suggested to propose a TF-based seizure detector. This detector, called TF matched detector, performs a two dimensional correlation between the EEG signal and a reference template selected as a model in TF domain of the EEG seizure.

15.5.7 Time-Frequency Matched Detector

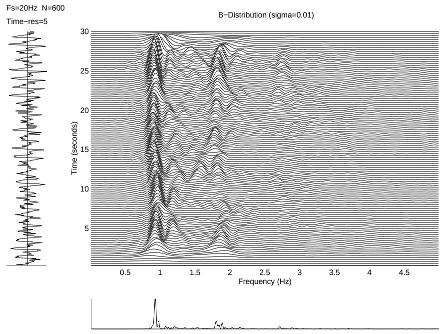
The matched filter is the simplest approach for constructing detectors and classifiers. It essentially reduces to a correlator receiver whose output is compared to a threshold. The threshold is chosen such that the probability of a false alarm is kept constant. The correlator receiver is implemented in time domain as a one-dimensional correlation between the received noisy signal $x(t)$ and a reference signal $s(t)$ or using the corresponding spectral representations. To extend this detector to handle nonstationary signals, the one-dimensional correlation is replaced by a two-dimensional correlation involving the TFD $\rho(t, f)$ of $x(t)$ and $s(t)$. The resulting test statistic is given by:

$$T(x) = \iint \rho_x(t, f)\rho_s(t, f)\, dt\, df \tag{15.5.2}$$

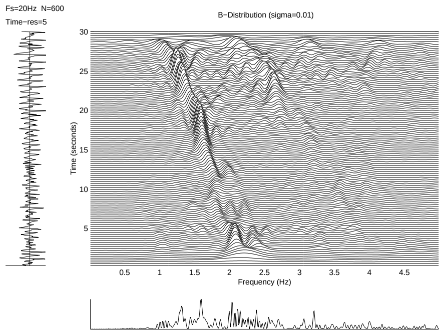
This type of detector has been implemented using different quadratic time-frequency distributions such as the spectrogram [6], the Wigner-Ville, and cross Wigner-Ville



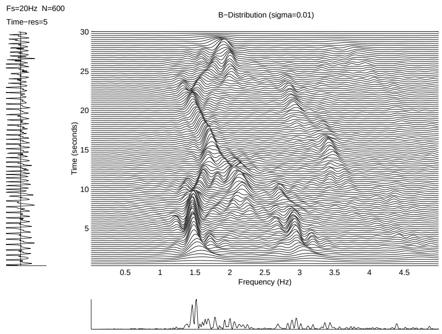
(a) Newborn seizure.



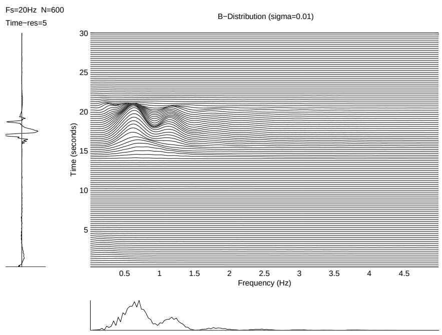
(b) Seizure exhibiting LFM behavior with constant frequency.



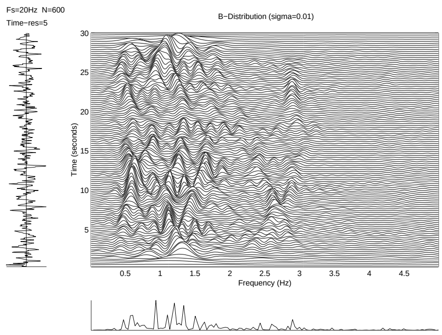
(c) Seizure exhibiting LFM behavior with decreasing frequency.



(d) Seizure exhibiting piecewise LFM behavior.



(e) Burst of activity.



(f) EEG lacking a specific pattern.

Fig. 15.5.1: B-distributions of EEG signals.

distributions [7] and the auto- and cross-ambiguity functions [8]. Using Moyal's formula, we get:

$$\iint \rho_x(t,f)\rho_s(t,f)\,dt\,df = \left| \int x(t)s^*(t)dt \right|^2 \tag{15.5.3}$$

This equality is only valid when the kernel filter is unimodular; that is its absolute value is equal to one all over the ambiguity domain. This is the case, for example, for the Wigner-Ville distribution and Rihaczek distribution [9]. Equation (15.5.3) is an alternative interpretation of the correlator receiver in terms of a correlation of the TFDs. Even though the B-distribution does not verify exactly Eq. (15.5.3), it has been used as the basis for the TF matched detector because of its superiority over the other TFDs in representing EEG signals as discussed in Section 15.5.4 (see also Articles 5.7 and 7.4).

For the case of a deterministic signal in additive noise (even white Gaussian noise) the TF-based correlator is suboptimal due to the nonlinearity of the quadratic TFDs which accentuates the effects of noise by introducing artifacts. To use a correlator receiver, it is usually required that the wave shape of the reference signal (or other related information such as its TFD) as well as the noise statistics are known. Section 15.5.6 indicated that the EEG seizure could be characterized by a linear or a piecewise linear FM. To construct a TF-based matched detector, a representative TFD of a linear or piecewise linear FM, $\rho_{ref}(t,f)$, is selected to serve as template (reference). The correlator statistic $T(x)$ used is the two dimensional cross-correlation between the EEG signal TFD and the reference signal TFD, i.e.:

$$\iint \rho_{ref}(t,f)\rho_z^*(t,f)\,dt\,df \tag{15.5.4}$$

where z is the analytic signal corresponding to the EEG signal under consideration.

15.5.7.1 Implementation of the Time-Frequency Matched Detector

The implementation of the TF matched detector and a description of its main components are described below. More details may be found in [10].

Preprocessing: This stage includes artifact (such as ECG, EOG, and EMG) removal, noise filtering, and resampling the signal to comply with detector input specifications. A low pass filter along with an artifact removal algorithm using adaptive signal processing techniques were implemented for this purpose [4].

Signal Restructuring: EEG is segmented into an array of signals of fixed length (2 minutes) to be suitable for performing the cross-correlation. Shorter signal lengths led to higher rates of miss detections and false alarms. Once the full input EEG signal is divided into blocks of 2 minutes duration, each block is stored as a row of the newly formed array of signals. A protocol of 50% overlap of each block was adopted.

Detection Loop: The detection loop is executed until all the blocks of the input EEG signal have been processed. An offset value is maintained, giving a precise location in the original signal where abnormal events are detected.

Cross-correlation: The cross-correlation between the TF array of the EEG signal and the template (mask) is obtained using the two-dimensional cross-correlation function given by Eq. (15.5.4). The most crucial process is the choice of the template, in this case (see Section 15.5.6) the TFD of a linear FM or a piecewise linear FM. The time duration of the FM signal is set to 20 seconds as discussed below. To find the optimum slopes of the FM signal IF, that is the ones that corresponds to the best detection rate, a testing stage is necessary [10]. A similar testing stage is also required to select an optimum threshold that realizes a good compromise between the rate of good detections and the rate of false alarms.

Amplitude and Length Criteria: Ideally there will be one peak value in the output of the cross-correlation array, with its output amplitude determining the presence or absence of seizure. This proved to be unreliable, and it was decided to perform a search of sequential series of values over the amplitude threshold defined earlier. This proved to be successful, and a minimum ridge length of 20 seconds over the amplitude threshold was classified as a seizure. The 20-second length adopted is larger than the minimum 10-second length of EEG seizure adopted by many neurologists [5].

Map Seizure Decision to Real Time Location: This stage simply ties all of the independent decisions on each block of processed signal (remapping any seizure decision to a time series function) of equivalent length to the input EEG signal. This output waveform consists of ones or zeros, where one indicates the presence of seizure at the corresponding time.

In order to validate and calibrate the detection algorithm, simulated data generated by the EEG model [2]. The model generates an EEG like signal characterized in time frequency by a linear IF with a random slope in the range of [-0.07 0]. These values were reported in [5]. The B-distribution was used to generate the reference template and the TFD of the simulated EEG. The signal used in the construction of the reference template is a linear FM. The average detection obtained was 99.1% while the false alarm rate was 0.4%. These results confirm the validity of the methodology since the template is well adapted to the EEG model.

15.5.8 Summary and Conclusions

The patterns obtained by a TF analysis of newborn EEG seizure signals show a linear FM or piecewise linear FM characteristic. This suggests a method of seizure detection and classification in the TF domain. A TF detector is proposed that involves cross-correlating the TFD of the EEG signal with a template. The design of the template takes into account the TF characteristics of the EEG seizure extracted in the TF domain. The performance of this time-frequency detector was tested on synthetic signals, corresponding to one specific type of seizure pattern (LFM). At

the time of publication, the methodology was being extended to deal with LFM patterns of varying slopes, and with piecewise linear FM patterns. The procedure will then allow classification within the selected sub-classes.

Another time-frequency approach to newborn EEG seizure detection is described in [11].

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